The rising tide lifts some interest rates: climate change, natural disasters, and loan pricing*

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Abstract

We investigate the effect of climate change, through natural disasters, on corporate borrowing costs. Using novel data, we construct granular measures of borrowers' exposure to various natural disasters. We disentangle the effect of lenders updating their believes about the future severity and frequency of climate change related disasters from the effect of direct disaster hits by focusing on firms that are at-risk, but not directly hit by disasters. Following a climate change related disaster, interest rates on loans of at-risk but unaffected borrowers spike both in the primary and secondary markets. Consistent with time varying attention to climate change, effects are amplified when attention to climate change is high, and there is no such effect for disasters that do not get worse with climate change. Borrowers with the largest exposure to climate change, and those with the least ability to absorb adverse shocks, suffer the highest increase in rates. Firms react by reducing investment and increasing cash reserves.

JEL Classifications: G21, Q51, Q54

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1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) forecasts that climate change will cost up to 10% of U.S. GDP annually by the end of the century (Hong, Karolyi, and Scheinkman, 2020). Climate change can have potentially devastating long-term economic effects (Stern, 2007), with the majority of climate change-related consequences expected towards the end of the century. The long delay before these effects fully impact the global economy can discourage actions to mitigate climate-related risks, and the relevance of these risks from today's perspective depends heavily on discount rates (Nordhaus, 2010). As a result, large parts of the literature on climate change and financial markets have concentrated on long lived assets such as real estate or equities (Giglio, Maggiori, and Stroebel, 2015; Murfin and Spiegel, 2020; Baldauf, Garlappi, and Yannelis, 2020), and focus on estimating discount rates to capture long run damages (Giglio, Maggiori, Rao, Stroebel, and Weber, 2018).

Our paper instead uses a novel channel by which climate change already shapes economic risks today, that is, through the increased frequency and severity of certain extreme weather events, and focuses on comparatively short lived corporate loans. A key challenge in linking climate change to corporate debt funding is that while most climate change-related consequences are projected to peak towards the end of the twenty first century, the average loan maturity is only 4 years. Consistent with this mismatch between the maturity of financial instruments and the long horizon of climate change, Addoum, Ng, and Ortiz-Bobea (2020) find no current effect of extreme temperatures on firms, and Goldsmith-Pinkham, Gustafson, Lewis, and Schwert (2019) find that investors have only very recently started to price projected long term sea level rises in municipal bonds.

The most straightforward approach to assessing the effect of climate change-related natural disasters on firms' borrowing costs is to analyze the loan spreads charged by banks after borrowers are directly hit by disasters. While this approach yields evidence of investors increasingly pricing disaster risk (see Figure 1), it cannot disentangle the direct effect of the disaster, such as disruptions of business and physical damage, from the updating in lender's expectation about the future frequency and severity of these disasters. In particular, as Nordhaus (2010) points out, measuring the direct reaction to disasters cannot account for changes in corporate exposure to affected regions.

Our identification strategy, instead, relies on observing changes in interest rates to borrowers with exposure to climate change-related disasters, but that were not directly affected by a specific event. We refer to these firms as *indirectly affected* borrowers throughout the paper. This approach allows us to isolate lenders' updated expectations on the future severity of climate change-related events. The staggered aspect of disasters also mitigates the concern that results are driven by potentially omitted and coinciding events.

We focus on severe weather events, or natural disasters, which climate scientists argue are already getting more severe today, specifically hurricanes.[1] These disasters are likely the first channel through which climate change is impacting borrowers and are, therefore, a perfect laboratory to overcome the long-term horizon challenge of climate change (Giglio et al., 2018). Importantly, these types of climate risks are already being priced by investors, as almost two-thirds of institutional investors surveyed by Krueger, Sautner, and Starks (2020) report that they expect the physical risks of climate change to affect their credit portfolios today or within two years. Beyond the impact of climate change on loan pricing, we also assess whether extreme weather events are already affecting firms' financial decisions, which would provide early evidence on the consequences of climate change dynamics on corporate actions.

We find that following climate change-related disasters, banks charge higher spreads on loans to *indirectly affected* borrowers that have large exposure to disasters, while not directly affected. This effect varies from 8.6 basis points for hurricanes to 9.7 basis points for wildfires and to 9.8 basis points for floods. These changes in loan spreads are economically sizable, as they represent about 5% to 6% of the unconditional risk premium in the sample. In our baseline specification, we focus on hurricanes, as they are widely observed, severe, and relatively frequent. Consistent with a non-linear effect related to exposures, the impact on loan spreads is concentrated among the borrowers with the largest exposure. Further, risky firms experience greater hikes in loan spreads, suggesting that the change in loan spreads is strongly related to borrowers' creditworthiness.

Providing additional support to the relation between weather events and climate change, we also find that the pricing of climate change-related disasters appears to be time varying with attention to this topic. The increase

[1] Hurricanes have become increasingly more severe in recent years and their landfall have caused higher damages in the United States (Nordhaus, 2010), with the 2020 storm season producing a record 29 named Atlantic storms. This pattern holds globally (Webster, Holland, Curry, and Chang, 2005), and is true for a range of other types of climate change-related severe weather events (Stern, 2007; Mendelsohn and Saher, 2011). Recent work has developed methods that allow for the attribution of individual disasters to climate change. Hansen, Auffhammer, and Solow (2014) directly attribute the increased severity of both floods (Van Der Wiel, Kapnick, Van Oldenborgh, Whan, Philip, Vecchi, Singh, Arrighi, and Cullen, 2017) and hurricanes (Risser and Wehner, 2017; Van Oldenborgh, Van Der Wiel, Sebastian, Singh, Arrighi, Otto, Haustein, Li, Vecchi, and Cullen, 2017) to climate change. The impact of these severe weather episodes is significant, and Stern (2007) estimates that extreme weather events alone could cause annual cost 0.5%-1% of global GDP by the middle of the century.

in spreads for at-risk borrowers is concentrated in the two years after the publication of major IPCC reports, and reaches up to 17 basis points during those periods of high attention. Consistent with time varying attention, pricing effects are strongest in the immediate aftermath of an indirect disaster hit and fade over time. This is in line with Goldsmith-Pinkham et al. (2019), who find evidence of an attention channel that increases the pricing of climate risk in municipal bonds due to elevated projections on sea level rises. Further, the reaction in loan spreads is stronger for more severe disasters that tend to be more visible and provide a greater chance for banks to update their beliefs about the severity and frequency of climate change disasters.

This evidence on the link between climate-related risks and loan pricing is not completely surprising, as it is consistent with lenders' awareness of the threats climate change poses to their loan portfolios. In recent regulatory filings, the ten largest U.S. banks discuss the link between climate change and certain severe weather incidents, and 8 out of 10 mention that climate change (potentially) intensifies these disasters and that they pose a material risk to the creditworthiness of borrowers (Appendix Table A.1). Lenders, credit rating agencies, and governments are aware of the threat of climate change related disasters for loans.[2]

Our baseline work focuses on the primary market for syndicated loans, but we also find that climate risks are priced in the secondary market. In that market, we observe a 1.7% decline in loan prices following recent climate-related natural disasters, providing evidence that climate change is impacting loan pricing beyond origination. This is important, as it suggests the decision to raise capital is not a driver of the observed increase in loan spreads. Moreover, this result suggests that investors beyond banks also price the climate risk embedded in these types of loans.[3]

After testing the effects on loan spreads, we assess whether climate risks forces firms to adjust their investments. We find that bank-dependent firms reduce their ratio of investment to assets by about a quarter of a percent, which is an economically sizeable effect. This finding provides further evidence that climate-related risks may already be affecting firms through their cost of funding.

[2]For example, PNC Bank's 2019 10-K filing explicitly states that "Climate change may be increasing the frequency or severity of adverse weather conditions, making the impact from these types of natural disasters on us or our customers worse. [...] we could face reductions in creditworthiness on the part of some customers or in the value of assets securing loans." Appendix A.2 provides a wide range of examples for this type of awareness of the link between climate change, disasters, and credit risk.

[3]As noted by Lee, Li, Meisenzahl, and Sicilian (2019), syndicated term loans are typically transferred to other types of non-bank investors after origination. Price changes in the secondary loan market therefore reflect the views of these investors, rather than that of the banks that originally underwrote the loan.

In our empirical tests, we exploit detailed geographic exposure data on a large cross section of U.S. borrowers from the National Establishment Time-Series (NETS) data in combination with the Spatial Hazard Events and Losses Database for the United States (SHELDUS) to create, for each borrower, their exposure to various types of disasters. This setup allows us to measure not just the direct impact of disasters affecting borrowers, but also borrowers' general exposure to certain types of disasters based on their operations in at-risk areas.

One potentially confounding factor with this identification strategy is that banks transfer capital from unaffected regions to those affected by natural disasters (Cortés and Strahan, 2017; He, 2019). The increased interest rates for indirectly affected borrowers could therefore simply reflect the decrease in loan supply due to this shift in capital. We, therefore, control for time varying, bank specific loan supply conditions in all our specifications, effectively drawing inference from firms that borrow from the same bank at the same point of time, with the only difference being that one of them has exposure to climate change-related natural disasters and the other does not. This setup alleviates concerns of the capital transfer channel driving our results.

Conceivably, natural disasters can afflict firms through a more widespread effect on the economy as a whole. To investigate whether our estimates truly reflect lenders' updating about climate change-related disasters, we repeat our main analysis with non-climate change-related disasters (i.e., earthquakes, tornadoes, and winter weather). Borrowers with indirect exposure to these non-climate disasters experience no changes in interest rates in either the primary or secondary loan market. Moreover, our estimates for banks' updates to the severity of climate change-related disasters hold when we simultaneously estimate the effects of both climate- and non-climate disasters. Consistent with banks learning about the severity of disasters, the reaction in loan spreads is stronger for more severe disasters.

An additional concern might be that large scale disasters, such as hurricanes and floods, ripple through the economy due to customer supplier links (Barrot and Sauvagnat, 2016), and that this effect is more concentrated among firms with similar exposure to disasters (geographical profiles) and for more widespread disasters (hurricanes) as opposed to localized disasters (e.g. tornadoes). We, therefore, conduct an additional test that directly controls for each borrowers exposure to disasters through their customer- supplier linkages and find that our estimates are unaffected.

To further rule out that our results are driven by capital transfers between directly affected and indirectly affected borrowers, or a widespread hit to banks' balance sheets from major disasters, we explicitly control for lenders' exposure to directly affected borrowers. Our findings that banks increase rates to indirectly affected borrowers remains unchanged. The results are also robust to a wide range of alternative model specifications, variations in the size-cutoff of disasters, different ways to quantify corporate geographic exposure, and variations in the definition of affected borrowers.

Our paper contributes to the nascent literature on how investors respond to climate change by providing estimates on changes in corporate loan rates around climate-related natural disasters for indirectly affected firms. Quantifying the market's perception of shifts in climate is important for corporate borrowers in their long-term capital allocation decisions. To the best our knowledge, this is the first study to directly link climate change to present day corporate loan costs. To date, the evidence for corporations is limited to long-lived assets such as equity securities. Notably, Engle, Giglio, Kelly, Lee, and Stroebel (2019) develop a new-based measure of hedging climate change risk in portfolios, and Ramelli, Wagner, Zeckhauser, and Ziegler (2019) find that investors reward firms that try to mitigate effect on climate change. Kruttli, Roth Tran, and Watugala (2019) find that markets are effective at pricing the direct effect of extreme weather shocks in stock prices and options. On the bank lending side, de Greiff, Delis, and Ongena (2018) investigate how banks are exposed to regulation outlawing fossil fuels, which is another type of climate risk typically referred to as "transition risk" (Financial Stability Board, 2020). Similarly, Seltzer, Starks, and Zhu (2020) and Ivanov, Kruttli, and Watugala (2020) find that firms with higher climate regulatory risk, as opposed to actual physical climate risk, face higher bond and loan yields, and Chava (2014) finds that firms causing more environmental polution face higher costs of capital.

The closest paper to ours is Goldsmith-Pinkham et al. (2019), who investigate the effect of elevated projections on sea level rises on the pricing of municipal bonds. Like us, they investigate the effect of a specific part of climate change on debt securities and find that sea level rises are priced only very recently and to a small extent. We add to these studies by examining how corporate borrowers are hampered by risks emanating from climate change.

Another contribution is that we provide estimates on the credit risk costs that banks assign to climate-related natural disasters. This assessment is crucial, as banks may have to enhance their risk-management practices related to climate risks, if such events become even stronger or more frequent over time. Relatedly, from the regulatory perspective, the fact that loan rate hikes around climate-related natural disasters are transitory implies banks may be inadequately provisioning for potential future climate-related loan losses, which can diminish banks' financial resilience and result in economy-wide adverse effects. Finally, we identify that climate change related natural disasters can be used as a method to understand the impact of climate change on the pricing of short-lived assets.

2 Hypotheses development

The most straightforward way to estimate the effect of climate change-related disasters on borrowing costs is by estimating regressions of loan spreads on the direct hit of a disaster. However, this approach faces the challenge that recent years have seen increasing economic activity in areas that are also prone to these disasters, for example Florida (Nordhaus, 2010; Pielke Jr, Gratz, Landsea, Collins, Saunders, and Musulin, 2008). The impact of disasters on loan spreads can be decomposed into two parts, the direct results of the disaster (e.g. damages to physical assets, disruptions in the production process), as well as lenders' updating on the future frequency and severity of these disasters. More formally, we can express these two components of climate change related disasters as follows:

$$Loan\ \ spread|hit \ = \ \mathbb{1}_{hit} \times severity \times exposure \times damage|hit + P(hit) \times exposure \times \mathbb{E}[severity] \quad (1)$$

When we observe the change in loan spreads for a directly hit borrower, we cannot disentangle the effect of the severity and exposure at the current point of time from the future expected severity and frequency (P(hit) and $\mathbb{E}[severity]$). To overcome this identification challenge, we isolate shocks to the expected future severity and frequency of climate change related disasters by drawing inference from firms that are *at risk* of these disasters, but not directly affected. Formally, we test:

Hypothesis 1: After climate change-related disaster, banks charge higher rates for at risk, but not directly hit borrwoers.

One potential issue with this setup is that banks might also update on the future exposure of borrowers to disasters (Nordhaus, 2010). We, therefore, contrast these results on climate change-related disasters with non-climate change-related disasters. We test:

Hypothesis 2: For disasters that do not get worse with climate change, the effect on interest rates for indirectly affected borrowers should be smaller and reflect only updating about the future exposure of borrowers.

Finally, we hypothesize that time-varying attention to climate change leads to fluctuations in the pricing of climate change disaster risk.

Hypothesis 3: The pricing of climate change-related disasters is more pronounced when attention to climate change is higher.

3 Data

3.1 Data on disasters

We obtain data on disasters from the Spatial Hazards Environmental Disasters for the United States database. The database provides information on date, duration, disaster types, damages, and the Federal Information Processing Standards (FIPS) code of all affected counties. This data is widely used in the study of the effect of natural disasters, including in studies on bank lending (Cortés and Strahan, 2017). We classify disasters as being related to climate change based on the most recent IPCC report (Seneviratne, Nicholls, Easterling, Goodess, Kanae, Kossin, Luo, Marengo, McInnes, Rahimi, et al., 2017). The report finds there is substantial evidence of a link between climate change and droughts, heatwaves, and wildfires today. The report finds similarly strong evidence for a link between climate change and more severe Atlantic hurricanes, and extreme precipitation. We, therefore, classify as climate change-related hurricanes, floods, and wildfires. In our baseline specification, we only consider hurricanes as climate change-related disasters, as they are widely observed, severe, and relatively frequent. In Appendix 5, we provide a large set of robustness tests for all our results using a pooled estimator that groups hurricanes, floods, and droughts jointly as climate change disasters. In addition, we show that results hold for each of these disasters individually.

The IPCC also finds little or no evidence for a link between climate change and tornadoes, and that climate change is associated with fewer extreme low temperatures (these disasters are coded as winter weather in SHELDUS). We, therefore, code winter weather and tornadoes as non-climate change-related disasters, and add to this group earthquakes, as those are clearly unrelated.[4] As earthquakes are the most clearly climate change unrelated type of disaster, our main specification uses only earthquakes as non-climate disasters. As for climate disasters, Appendix 5 provides tables showing the full robustness of our results to considering these three non-climate disasters individually or jointly.

We focus on large disasters with aggregate damages exceeding $100 million in 2016 constant dollars and calculate for each county their exposure to each disaster for a rolling ten year window. We then classify counties as high-exposure counties if they are located in the top 10% of counties with respect to damages for a certain type of disaster within that window. Table A.9 shows that effects are larger when we limit ourselves to larger, more severe disasters.

3.2 Other data

To quantify each borrower's exposure to climate change-related disasters, we construct granular corporate geographic footprints. Deutsche Bank, in its 2018 white-paper, captures this intuition. "Perhaps the most telling metric of a company's climate risk is the location of its assets and their exposure to changing extreme weather patterns. The geographic areas on which a company depends to produce, manufacture, deliver, and sell goods, are a powerful indicator of its fundamental exposure to future climate risks."[5] We construct detailed geographic footprints of corporations using Dun and Bradstreet's National Establishment Time Series data (NETS). We use the county level data on the number of establishment locations to create a location-weighted measure of a company's exposure to each disasters. To do so, we multiply each firm's fraction of establishments in each county with that county's exposure to disasters, arriving at an operations-weighted exposure to disasters measure. We then classify firms as indirectly exposed to each type of disasters (e.g. hurricanes) if its operations weighted exposure to historically disaster (hurricane) prone counties is in the top quartile of firms.

We add syndicated loan data from Reuters Loan Pricing Corporation (LPC) Dealscan and accounting data

[4]While the evidence is strong that climate change leads to a reduction in extreme low temperatures, it is more mixed with respect to tornadoes. Interestingly, we find that tornadoes are priced by the market somewhere between climate change-related and the other -unrelated disasters, potentially reflecting this uncertainty.

[5]A detailed overview of this and similar statements by other lenders is presented in Appendix A.2.

from Compustat. Dealscan provides loan information at the origination, including loan amount, loan maturity, loan spread, etc. Our sample starts from 1990 with loans in the United States that can be matched with NETS data on the borrower side. We also adjust loan amounts to dollar value in 2016, using the GDP deflator of the Bureau of Economic Analysis. Syndicated loans have one or more lead arrangers and several participating lenders. A lead lender serves as an administrative agent that has the fiduciary duty to other syndicate members to provide timely information about the borrower, whereas participating lenders are passive investors, whose main role is sharing the ownership of a loan. So, we restrict our analysis to lead lenders.

Table 1 displays summary statistics of loan characteristics and natural disaster property damages. Our sample period is from 1990 to 2014. All variables are calculated as defined in Appendix A.1.

[Table 1 here]

Panel A covers all matched loans in our sample. The median loan is a $143.75-million credit package with four-year maturity and 166.26 basis points as credit spread. More than half of the loans have financial covenants, over three-fourths of the loans are revolving credit facilities. The median borrower in the sample has $2.27 billion in total assets, with an ROA of 0.12 and a debt to asset ratio of 0.32. More than half of loans are issued by firms that are classified as indirectly exposed to climate- or non-climate-related disasters in a given month. 42% of the loans are issued within three months after a climate-related disaster occurs, 27% of the loans are issued within three months after a non-climate-related disaster occurs.

Panel B shows disaster damages across types. Hurricanes and flooding affect more than 1300 counties due to their massive scale. Though severity varies by type, all of the disasters in our sample are severe because we focus on large disasters with aggregate damages exceeding $100 million in 2016 constant dollars. On the county level, all types show significant damages in the tails of the distribution.

4 Results

4.1 Empirical setup

Our goal is to link climate change induced disasters to loan outcomes. The most straightforward approach is to estimate whether the *direct* impact of climate change disasters has increased in recent years. Figure 1 presents this analysis.

[Figure 1 here]

The effect of direct hits by climate disasters on interest rates indeed appears to exhibit a positive time trend. This direct approach, however, does not allow to disentangle changes in the magnitude of the direct effects of the disaster from the effect of the disasters becoming stronger.

For example, damages from hurricanes have been increasing partly because more people live in hurricane areas with more valuable property (Pielke Jr et al., 2008). Direct exposure to large weather events has widespread impact on economic and business activity (Dell, Jones, and Olken, 2014), making it difficult to isolate learning about climate change. The key endogeneity challenge is therefore to distinguish the effect of direct impact of natural disasters form that of adjusted expectations of future natural disasters due to climate change.

The increasing reaction in interest rates after a direct hit by a climate change disaster therefore reflects both the increase in actual damages, as well as a potential learning about increased climate change risk.

To disentangle the direct effect of a hit by a natural disaster from the indirect effect of lenders learning about increased risk of climate change induced disasters, we draw inference not from firms that are actually hit, but instead firms that are at risk of climate change disasters, without actually experiencing damage.

Intuitively, our hypothesis is that banks learn about the increased severity of climate change induced disasters by observing them. For example, a bank lent money to a borrower with major operations in a hurricane prone region, such as Florida. When hurricane Harvey hit Houston in 2017, this borrower is not directly affected by the damage. However, if the lender updates its prior regarding the severity of hurricanes after observing Harvey, it will still charge a risk premium for the next loan of the borrower in Florida. Formally, our econometric setup in its most complete form can be described by equation 2 below.

$$Spread_{i,m,t} = \beta_1 Indirect\ hurricane_{i,t} \times Recent\ hurricane_t + \beta_2 Indirect\ hurricane_{i,t} + \beta_3 Recent\ hurricane_t + \beta_4 Direct\ exposure\ disaster_{i,t} + \gamma X_{i,m,t} + \alpha_i + \phi_{m,t} + \epsilon_{i,m,t} \quad (2)$$

The outcome variable of interest is the interest rate spread charged to borrower i by bank m in year t. Our main coefficient of interest is β_1. It measures the effect of $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$, the interaction of our time varying measure of firm i's exposure to climate related disasters with an indicator of a recent disaster of that type. If banks update their prior on the severity of climate change induced disasters after observing them, we expect β_1 to be positive.

Larger exposure to climate change related disasters might reflect time varying levels of riskiness, for example expansion into new markets. We, therefore, control for $Indirect\ hurricane_{i,t}$. The indicator *Recent hurricane* takes the value of one if a climate disaster has happened within the last 12 months prior to loan origination. It is, therefore, not absorbed in the year fixed effects. Since most of our sample firms have geographically far-flung operations, most larger natural disasters such as hurricanes have at least a small impact on most borrowers. We, therefore, control for *Direct exposure disaster*, a measure of direct exposure to disasters analogous to *Indirect hurricane*.

Borrowers with more indirect exposure to hurricanes might be different from others on unobservable dimensions. We, therefore, include α_i, borrower fixed effects, into our estimation. In effect, we compare two loans taken out by the same borrower, one during normal times and another after a disaster struck recently to which the borrower has indirect exposure. Importantly, these borrower fixed effects absorb a number of alternative explanations, such as the geographic location of a firm's operation or the industry in which it operates.

Another potentially confounding channel is the bank-capital channel. Large disasters drain funds from banks, and the rising interest rates for unaffected borrowers might reflect this capital channel (Cortés and Strahan, 2017). We, therefore, include bank × year fixed effects ($\phi_{m,t}$) in our regressions. Intuitively, this means we are comparing two borrowers from the same bank, in the same year, with the difference being their indirect exposure to a recent climate change disaster. The within-lender-time comparison is central to our empirical strategy. To properly capture this effect, if a loan has more than one lead lender, we include all borrower-lender pairs into our estimation. Finally, we include $X_{i,j,t}$, a vector that reflects a wide range of time-varying firm (size, profitability and debt to asset) and loan controls (loan type, maturity, covenants).

4.2 Climate change and loan pricing

Table 2 presents the results from estimating various forms of equation 2.

[Table 2 here]

The key coefficient in this specification is β_1, the effect the interaction of our time varying measure of firm i's exposure to climate related disasters with an indicator of a recent disaster of that type. In column 1 of Table 2, the coefficient estimate of $Indirect\ hurricane_{i,t} \times Recent\ hurricane_t$ is 8.6 basis points, and statistically significant at the 5% level. This result suggests that, after a climate change related natural disaster, banks raise interest rates to borrowers with high exposure to this type of disaster. The economic magnitude of this effect is sizeable and is comparable to a credit rating downgrade by about one notch.

We include firm (borrower) fixed effects in this specification, which control for unobservable, borrower level heterogeneity in loan prices. To avoid intra-bank capital transfers driving our results, we control for Bank × year fixed effects, which means our inference effectively stems from comparing two borrowers of the same lender in the same year. Finally, we control for the degree to which each borrower is directly affected by climate change related natural disasters.

All specifications in Table 2 include the un-interacted measures of firm's indirect exposure to climate related disasters ($Indirect\ hurricane_{i,t}$) and recent disasters in the prior 12 months ($Recent\ hurricane_t$). These two measures are largely subsumed by the borrower and time fixed effects, respectively, and not statistically or economically significant.

In column 2, we add loan level controls for maturity, loan type and the presence of financial covenants. Our main coefficient estimate remains economically and statistically very similar, at about 8.1 basis points. The same is true when we replace these loan controls with firm level control variables that capture time-varying firm level credit quality. These controls include profitability, leverage, and credit rating. The estimate for β_1 in this setting is 8.9 basis points and is statistically significant at the 5% level.

Column 4 presents our most complete specification, that includes the full set of fixed effects, bank controls, and loan controls. The coefficient estimate of β_1 in this specification is about 8.6 basis points, and statistically significant at the 5% level.

Taken together, the results in Table 2 imply that banks update their expectations regarding increased future damage from climate change related disasters by increasing the interest rate spread charged to borrowers with significant exposure to these disasters.

One concern is that these estimates reflect banks updating on disasters more generally, and not updates on climate change in particular. Table 3 repeats the analysis from Table 2, but replaces our measures of direct and indirect exposure to *climate change related disasters* (hurricanes) with analogous measures for *non-climate change related disasters* in the form of earthquakes. These include earthquakes, tornadoes and winter weather.[6]

[Table 3 here]

In column 1, the estimated coefficient on $Indirect\ earthquake_{i,t} \times recent\ earthquake_t$. The coefficient estimate is statistically insignificant and actually negative -4.2 basis points, in contrast to the positive one on climate change related disasters of 8 basis points. As we add the various controls for firm and loan level variables in columns 2 to 4, the coefficient estimate on β_1 remains negative, statistically insignificant, and economically small throughout.

This result supports our interpretation of the results in Table 2. Climate change makes certain disasters more sever over time. Banks learn about this increase in severity through observations, and update the risk premium for at-risk borrowers accordingly. While non-climate change related disasters are similarly devastating for borrowers, they do not get more severe over time, and banks already price them in their loans correctly.

In a final test, we rule out that our results are driven by potential simultaneous occurrence of both climate- and non-climate change related disasters. In Table 4, we simultaneously control for the effects of both climate change related (hurricanes) and non-climate change related disasters (earthquakes).

[Table 4 here]

[6] As described in section 3, we follow the IPCC guidance in classifying disasters into climate change related and -unrelated events. Our results are robust to variations in this definition and we include regressions for each individual disaster in Appendix 5. All results are robust to using each disaster individually as well as pooling all climate- and non-climate change disasters.

As in out main analysis, we find that the effect of climate change disasters on firms with general exposure to these disasters is associated with a statistically and economically large increase in interest rates of about 9 to 10 basis points, even after controlling for simultaneously occurring non-climate change disasters. As in the analysis in Table 3, the coefficient on $Indirect\ earthquake_{i,t} \times recent\ earthquake_t$ is small, negative, and statistically insignificant throughout all specifications.

These results support the idea that banks learn about increasing severity of climate change related disasters and increase the interest rate charged to borrowers at risk of these disasters.

4.3 Climate change is priced more severely for borrowers under financial distress

Increased borrower risk hurts banks mostly through the threat of default. A borrower that is financially healthy can weather the damages from climate change induced disasters without an impact on their ability to repay debt. In contrast, borrowers that are close to bankruptcy are most at risk of defaulting on loans as a result of climate change induced disaster risk. If banks indeed price the increased risk from climate change related disasters, the price reaction should be most pronounced in borrowers that are more at risk of bankruptcy. We empirically test this conjecture in Table 5 using two proxies for borrower risk.

[Table 5 here]

First, in column 1, we estimate the most saturated model of Table 2, column 4, and interact $Indirect\ hurricane \times Recent\ hurricane$ wit *high leverage*, an indicator that takes the value of 1 for firms with high leverage. Analogous to our definition of *indirect hurricane*, we define high leverage as being in the highest quartile of the distribution of leverage in our sample. The interaction term $Indirect\ hurricane \times Recent\ hurricane \times high\ leverage$, therefore, captures the differential effect of an indirect hurricane hit on firms that are particularly at risk. Consistent with banks reacting more pronounced when borrowers are less financially stable, we find that the coefficient on the triple interaction is 21.5 basis points and statistically significant at the 10% level. This effect is almost three times as large as the effect in the overall sample. The estimated coefficient on $Indirect\ hurricane \times Recent\ hurricane$ captures the effect of an indirect hurricane hit on firms without high leverage. It is economically smaller than in our main specification at only 4 basis points, and statistically insignificant. This result suggests that banks price climate change induced disaster risk mostly for the at-risk borrowers.

In column 2, we measure financial stability through credit ratings. The indicator *noninvestment grade* takes the value of one for firms rated below investment grade (BBB). The coefficient on the interaction term $Indirect\ hurricane \times Recent\ hurricane \times Noninvestment\ grade$ is 26.7 basis points and statistically significant at the 5% level. This result again is consistent with banks pricing climate change risk more intensely when the shocks from climate change-induced disasters are more likely to impact borrowers' ability to repay. As in column 1, the coefficient on *Indirect hurricane* × *Recent hurricane* is 6 basis points, close to our overall sample estimate but statistically insignificant.

These tests support the conjecture that banks react particularly sensitively to increased climate change induced disaster risk when it is more likely that borrowers cannot absorb these risks, and they eventually accrue to the lender.

4.4 More severe disasters are associated with stronger market reactions

If climate change impacts both the frequency and severity of disaster, market participants should react more strongly to more sizeable disasters for two reasons. First, more severe disasters are more easily observed, and hence priced. Since we estimate the effect of disasters on indirectly affected borrowers, a lender might potentially fail to update their risk assessment since they fail to observe smaller disasters. Larger disasters receiving national attention are more easy to observer, and hence lenders update more strongly after large disasters.

The second potential channel linking disaster size and the climate change risk premium in lending is that larger disasters make lenders update more strongly about the trend in disaster magnitude. Since climate change disaster damage has both a random component and an increasing time trend, lenders can more easily assign infer a trend in increasing disaster strength for large disasters, whereas for smaller disasters they might assign damages to random fluctuations.

Ultimately we cannot differentiate between these two explanations, but either one predicts that larger disasters should be associated with more significant pricing pricing effects.

We test this conjecture in Table 6. In our main analysis, we consider all disasters with cumulative damages in excess of $100 million to define our measure of disaster exposure. In the following tests, we analyze whether more severe disasters are associated with more significant market reactions. To do so, we separately calculate our measure of exposure for cutoffs of \$100 million and \$200 million. We estimate our baseline specifications with each of these definitions separately in Table 6.

[Table 6 here]

As Table 6 shows, when our analysis focuses on larger disasters in excess of \$200 million in damages, the estimated coefficient on $Indirecthurricane \times recenthurricane_2 00mil$ becomes economically larger at 10.3 basis points. This result is consistent with lenders charging higher climate change risk premia after observing larger disasters.

4.5 How is climate change risk prices in the secondary market?

In this section, we investigate whether increasing disaster severity caused by climate change impact not only loan pricing at origination, but also in the secondary market. The loans observed in the primary market reflect both the decision to raise capital, as well as the lenders' assessment of risk. Increased loan spread at the time of initial borrowing could therefore be partially explained by selection concerns. For example, at risk borrowers might avoid raising debt after a disaster, hoping that financing conditions will be more favorable in the future. Those who do raise capital are the borrowers most desperate for capital, which is why they pay a higher risk premium. On the other hand, it could be that affected borrowers are shut out of credit markets and are unable to raise capital at any price for a while, which would mean that only the economically stronger borrowers can access capital markets shortly after an indirect disaster hit. In this case, the increased spreads for newly originated loans in our main analysis would under-estimate the true effect of disasters. Which of these two channels prevails is ultimately an empirical question.

To investigate the effect of selection in primary loan markets on our results, we turn to the pricing of loans in the *secondary* loan market. Since these are prices for already outstanding loans, there are no selection concerns. We obtain secondary market loan prices from Refinitiv's Loan Pricing Corporation. The secondary market data consists of self-reported information from brokers that quote daily prices on loans. The volume of trading in the secondary market has increased substantially in recent years (Beyhaghi and Ehsani, 2017), and we are able to obtain pricing information for 1737 loans from 2001 to 2016.

The secondary loan market is generally iliquid, and while brokers quote daily prices, there is no information on whether trades actually took place. To avoid drawing inference from stale prices, we aggregate quotes for each loan on the weekly level. We then test in an event study setting the price reaction of these loans for firms that suffer an indirect hit by natural disasters.

[Table 7 here]

In Table 7 we measure price impact along four separate dimensions. The outcome variable in column 1 is each loans un-adjusted mid-quote. Since loans often are issued below par, we take the ratio of this number with respect to each loan's first quote . In column 2, we replace this with the logarithm of the mid-quote. Since higher interest rates are the equivalent to lower loan prices, a negative coefficient in these specification of loan prices would be the secondary market equivalent to the higher initial loan yields in the primary market studies earlier. Our regressions control for both observable and unobservable loan characteristics through loan fixed effects, as well as time effects through year fixed effects. To make sure our results are not driven by within-loan time trends in prices, we cluster standard errors at the loan level.

The results in Table 7 confirm our findings from the study of loan spreads at origination. The mid quote of secondary market loans of at-risk borrowers drops by 1.7 percent relative to its initial quote in the wake of a recent hurricane. The coefficient estimate on the logarithm of loan prices is almost identical, at -1.7. Just like primary market participants price increased climate change risk through higher loan interest rates, secondary market participants therefore price it through lower prices for existing loans.

These results show that investors in the secondary market are pricing climate change risk through increasingly severe natural disasters. The economic magnitude of these estimates is significantly larger than the estimates of the primary loan market. A back of the envelope calculation linking changes in yield to changes in price suggest that an increase in annual yield of about 9 basis points, taken at median loan maturity of about 5 years, translates into a change in loan price of about half a percentage point. The estimates from the secondary market are about three times as large. This finding suggests that the most severely affected borrowers do not originate new loans in the primary market shortly after a disaster, either voluntarily or because they are shut out of the market. Consistent with this interpretation, we find a substantial drop in the liquidity in the secondary loan market following climate change disasters, with bid ask spreads widening substantially above their normal level.[7] Jointly, these findings from the secondary loan market do not just provide an independent verification of our primary loan market results, but also hint towards an effect of climate change induced disasters on loan *access*, which goes beyond our main results on loan pricing.

4.6 Attention to climate change is driving banks' lending decisions

Banks' ability to correctly price climate change induced risk depends on their ability to observe it. There is wide spread evidence that investor attention is limited, and can be focused by large events.

We, therefore, test whether there is time variation in bank's pricing of climate change-induced lending risk. We exploit the high profile publications of climate change reports by the IPCC as catalysts for banks' attention to climate change. These reports, which are published every six years, in 2001, 2007 and 2013, create substantial attention globally, which significantly increased attention to climate change (Goldsmith-Pinkham et al., 2019).

In Table 8 we present these cross sectional tests:

[Table 8 here]

These tests are similar to those in our main specification, except for the addition of the term $Indirect\ hurricane_{i,t} \times recent\ hurricane_t \times IPCC$, where $IPCC$ is an indicator taking the value of one in the 12 months following the publication of a major IPCC report. If banks pay more attention to climate change following these reports and adjust interest rates more substantially for borrowers with exposure to climate change related disasters, we expect the coefficient on this interaction term to be positive.

In column 1 of Table 8, we find that the estimated coefficient on the triple interaction $Indirect\ hurricane_{i,t} \times recent\ hurricane_t \times IPCC$ is indeed positive at 15.9 basis points, and statistically significant at the 5% level. Our main coefficient on $Indirect\ hurricane_{i,t} \times recent\ hurricane_t$ remains statistically and economically very similar to our main specification, at 9.6 basis points. This result suggests that banks indeed update interest rates more decisively following high profile public disclosure of IPCC climate change reports.

[7]Unfortunately, our data does not allow us to directly observe trading volume itself, which would be a more direct measure of liquidity.

As we add loan and firm level time control variables through columns 2 to 4, the estimated coefficients remain largely similar, although the estimate for $Indirect\ hurricane_{i,t} \times recent\ hurricane_t \times IPCC$ becomes slightly larger, with coefficient estimates between 25 and 17 basis points. The estimate on $Indirect\ hurricane_{i,t} \times recent\ hurricane_t$ becomes slightly smaller at around 8 basis points, but remains statistically significant at the 5% level except in column 2. These results imply that the majority of banks' adjustment to climate change is concentrated in the time periods when public attention to the topic is highest.

Previous studies have found that both equity investors (Choi, Gao, and Jiang, 2020; Alok, Kumar, and Wermers, 2020) and corporate managers (Dessaint and Matray, 2017) can overreact to salient impressions of climate change and extreme weather. Our findings imply that lenders might be subject to similar recency bias when pricing climate change risk.

To further investigate if attention to climate change disasters is time varying, we directly estimate the development of interest rates relative to an (indirect) climate change disaster shock. Table 9 presents the results of estimating our main model dynamically.

[Table 9 here]

The coefficient of interest is $Indirect\ hurricane \times recent\ hurricane\ (t\ quarters\ prior)$, the interaction of two indicators that take the value of one for firms that were classified as high-exposure to hurricanes and an indicator for the recent occurrence for a hurricane t quarters before the loan was issued. Analogously, $recent\ hurricane\ (t\ quarters\ future)$ is an indicator for loans taken out t quarters before a hurricane strikes.

The results in Table 9 are consistent with time varying, transient attention to climate change: While the coefficient estimate is positive and statistically significant for the quarter of the hit and the subsequent 4 quarters, the effect vanishes after about 1.5 years. These findings are consistent with salient information processing by lenders, similar to CEOs overreacting to direct hits by natural disasters (Dessaint and Matray, 2017).

We then repeat this estimation using secondary loan prices. Companies only issue new loans sporadically, and there are few observations of firms issuing a new loan shortly after having issued another one. The secondary loan market with its daily quotes allows us to study the time trend of loan prices at a more granular level. As before, we aggregate loan prices on a weekly level and estimate whether the initial price reduction we document in Section 4.5 are permanent. To this end, Table 10 estimates separate coefficients for each week following a hurricane.

[Table 10 here]

We find that loan prices of at risk borrowers initially drop by about 1.5 percent following a recent hurricane. However, this drop in prices only persists for about 6 weeks, and secondary market participants do not price these loans differently from before afterwards. These results in the secondary market are consistent with those in the primary market that suggest that the increased risk of natural disasters caused by climate change seems priced mostly when it is salient.

While these findings are consistent with salience, we cannot fully rule out another interpretation. Borrowers that are at risk of hurricanes and observe their increasing severity might actively relocate their operations out of harms way, similar to observed behavior in international supply chains (Pankratz and Schiller, 2019). If such a relocation is fast, it could partly explain the transient nature of our finding.

4.7 Ruling out alternative economic explanations

Our results that banks adjust interest rates for borrowers with exposure to climate change related disasters could be driven by a bank capital channel, where banks ration credit and increase interest rates to borrowers in unaffected areas, to supply credit to directly affected borrowers (Cortés and Strahan, 2017). While our $Bank \times year$ fixed effects in the main specification absorb these contemporaneous shocks, we conduct an exercise in Table 11 in which we explicitly control for banks' disaster exposure. Table 11 repeats our most main specification with both the pure fixed effects setting (columns 1 and 3) as well as the complete specification (columns 2 and 4).

[Table 11 here]

In addition, these regressions control for the lending bank's exposure to disasters both in the form of the total number of affected loans by this lender (columns 1 and 2) and the total amount of these loans (columns 3 and 4). We find that our estimate for $Indirect\ hurricane_{i,t} \times recent\ hurricane_t$ remains economically and statistically almost unchanged to the estimates in Table 2 at aroudn 8 to 10 basis points. The estimate for our measures of bank exposure are about +3 basis points, and statistically marginally significant columns 1 and 3. These results suggest that, while there's slight evidence of banks increasing interest rates following natural disasters, this increase does not drive the increased spread for borrowers with indirect exposure to climate change related disasters.

Another potential channel for our results could be that they reflect disaster spillovers across supply chains (Barrot and Sauvagnat, 2016). Table 12 tests this conjecture using data from (Barrot and Sauvagnat, 2016) on specific customer supplier links, to quantify the degree through which borrowers are affected by disasters through their supply chain. As before, odd (even) columns present estimates from the fixed effects only (most complete) specifications.

[Table 12 here]

We control for customer exposure (columns 1 and 2) supplier exposure (columns 3 and 4) and both (columns 5 and 6). Throughout all specifications, our main coefficient estimate $Indirect\ hurricane_{i,t} \times recent\ hurricane_t$ remains between 8 and 10 basis points, and statistically significant at the 5% level. We find that neither supplier nor customer disaster exposure impact interest rates statistically significantly in any of the saturated specifications. These results alleviate concerns that our estimates capture the network ripple effects caused by natural disasters along the supply chain.

4.8 Does climate change risk affect firm investment?

In our final set of results, we investigate whether climate change induced risk impacts corporate investment and cash holdings. To test this, we construct an annual panel of corporate investments and estimates model linking investment to indirect hits from climate disasters. Our outcome variable is the investment ratio, i.e. the ratio of each firm's investment to its assets, as well as cash holdings as a fraction of liabilities. We present the results in Table 13.

[Table 13 here]

We hypothesize that those firms most dependent on bank financing are going to react most severely to an indirect climate disaster hit. As before, we identify these firms by a lack of investment grade credit rating. Those are also the firms that experience the largest increase in financing costs, as shown in table 5.

Our results are consistent with climate change induced natural disasters having real effects on firms. In column 1 of Table 13, we saturate our model only with firm fixed effects. After an indirect hurricane hit, firms reduce relative investment by about 0.26% compared to the same firm's investment in other years, an economically sizeable effect of about 5% compared to the unconditional mean. In column 2, we add time fixed effects to account for time varying capital supply conditions, and in column 3 we add additional firm controls for size, profitability, and leverage. The finding that firms with less access to public capital markets due to the absence of an investment grade credit rating reduce investment by about 0.28% after an indirect climate disaster hit remains robust in all of these specifications. Compared to the unconditional sample mean investment rate of 2.15%, our coefficient estimates imply an economically sizeable reduction in investments by almost 10%.

Finally, in columns 4 to 6, we investigate if lower investment by particularly affected firms is accompanied by higher pre-cautionary cash holdings. We find that, after an indirect climate change related disaster, firms increase their cash reserves by about 2.2%. This estimate represents an economically large relative increase of 5% compared to the unconditional sample mean of 45%. These results show that not just lenders, but also firms react to an indirect climate change related disaster. Indirectly affected firms reduce investment and increase cash reserves, consistent with updated expectations of increased frequency and severity of climate change related natural disasters in the future.

4.9 Additional tests

We perform a series of additional tests with respect to data definitions in Appendix A.2.

In further tests, we repeat our main analysis separately for each climate and non-climate change disaster. Following the IPCC, we classify floods and wildfires as disasters that have increased in severity due to climate change. Appendix Tables A.2, and A.3 show that results are robust in these individual regressions. The coefficient estimates on $Indirect\ flood_{i,t} \times recent\ flood_t$ is about 9 basis points across the various specifications. The coefficient estimate on $Indirect\ fire_{i,t} \times recent\ fire_t$ is very similar at about 8 basis points. Both of these estimates are very comparable to the coefficient estimate of hurricanes in our main Table 2.

Similarly, we consider tornadoes and winter weather as non-climate change related disasters (in accordance with the IPCC). When we estimate our main specification with these disasters rather than earthquakes, the coefficient estimate on $Indirect\ winter\ weather_{i,t} \times recent\ winter\ weather_t$ is negative, and both economically and statistically insignificant, just like the coefficient estimate on earthquakes in Table 3. The third group of disasters in the non-climate change group are tornadoes. These disasters are less clearly separated from climate change than earthquakes and winter weather. The IPCC reports mixed findings on whether tornadoes increase in frequency or severity due to climate change, and in addition tornadoes frequently are a by-product of hurricanes. Consistent with this mixed status, the coefficient estimate on $Indirect\ tornado_{i,t} \times recent\ tornado_t$ is somewhere in between that for our pure climate change and non-climate change disasters at about 7 basis points, and marginally statistically significant in some specifications.

Alternatively, to estimate the effect of climate and non-climate related disasters individually, we can pool the three disasters in each group. Table A.6 reports the coefficient estimates from doing so for hurricanes, wildfires and floods. The coefficient estimate on $Indirectdisasters \times recentdisasters$ ranges from 6 to 8 basis points, slightly smaller than in the individual disaster regressions.

In a similar analysis, Table A.7 shows that pooling earthquakes, winter weather, and tornadoes yields a coefficient estimate that is statistically insignificant, although it is small and positive, driven by the hybrid status of tornadoes as somewhere between climate- and non climate change disasters. These results hold when we estimate coefficients on the two groups jointly in Table 4.

While hurricanes are large natural disasters, most of the other disasters can often cause smaller damages. This difference allows us to estimate the differential effect of disaster size on loan pricing reactions in more granularity than in Table 6. In Table A.9, we separately estimate the effect of $Indirectdisasters \times recentdisasters$ for disasters with a minimum damage of \$50 million, \$100 million, and \$200 million. We find that the coefficient estimates increase monotonically with disaster size, from 3 basis points to 6 basis points to 9 basis points.

We then perform robustness exercises with respect to the classification of disasters and borrower exposure. First, we replace our measure of geographic exposure from *location* weighted to *employment* weighted in Appendix Table A.10. The coefficient estimate for $Indirect\ disaster_{i,t} \times Recent\ disaster_t$ is almost unchanged compared to our main analysis with estimates ranging from 6 to 7 basis points.

Second, in Table A.11, we re-define the indirect exposure indicator as the top quintile (rather than top quartile) of firms of indirect exposure. Our coefficient estimate for the interaction of indirect exposure and recent disaster remains almost unchanged at around 6 to 8 basis points.

In an additional exercise, Table A.12 varies our measure of indirect exposure by taking into account the top 20% of firms based on exposure in a rolling 10 year window, as opposed to the top 10% in our main test. Our coefficient estimate for $Indirect\ disaster_{i,t} \times Recent\ disaster_t$ in this specification is about 8 basis points, and statistically significant at the 5% level across all four specifications.

The coefficient estimate on $Indirect\ disaster_{i,t} \times Recent\ disaster_t$ is statistically and economically essentially zero across the four specifications, which supports the robustness of our earlier estimates.

5 Conclusion

We investigate an early channel through which climate change impacts companies: the link between climate change-related natural disasters and bank lending. To overcome the simultaneity challenge between direct disaster damage and updates in banks' expectations of future disasters, we estimate reactions in loan spreads for borrowers that are at-risk, but not directly affected by disasters. Banks charge about 8 basis points, or 6% of the unconditional loan spread, higher rates for these indirectly affected borrowers.

These effects are strongest for borrowers which are least able to internalize a potential adverse shock, and more pronounced for more severe disasters. Consistent with time varying attention to climate change, this effect is concentrated in periods of high attention and reaches 17 basis points in years after the publication of major IPCC reports. Consistent with an attention channel, the effect of recent natural disasters is strongest shortly following the disaster.

Our findings provide the first evidence that climate change effects lending conditions for borrowers in the corporate lending market already today, through the increasing severity of natural disasters. Many questions remain for future research, first and foremost whether firms and banks shift their operations away from regions affected by climate change disasters.

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Figures

Figure 1: Direct exposure to climate change related disasters over time
The figure presents the effect of direct exposure to climate change related disasters over time. Climate change related disasters are defined as hurricanes, wildfires and floods. Direct treatment is defined as firms being in the top 20% of firms based on operations-weighted exposure to counties with direct hits by climate change related disasters. Vertical lines represent 90% confidence intervals clustered by borrower and year.

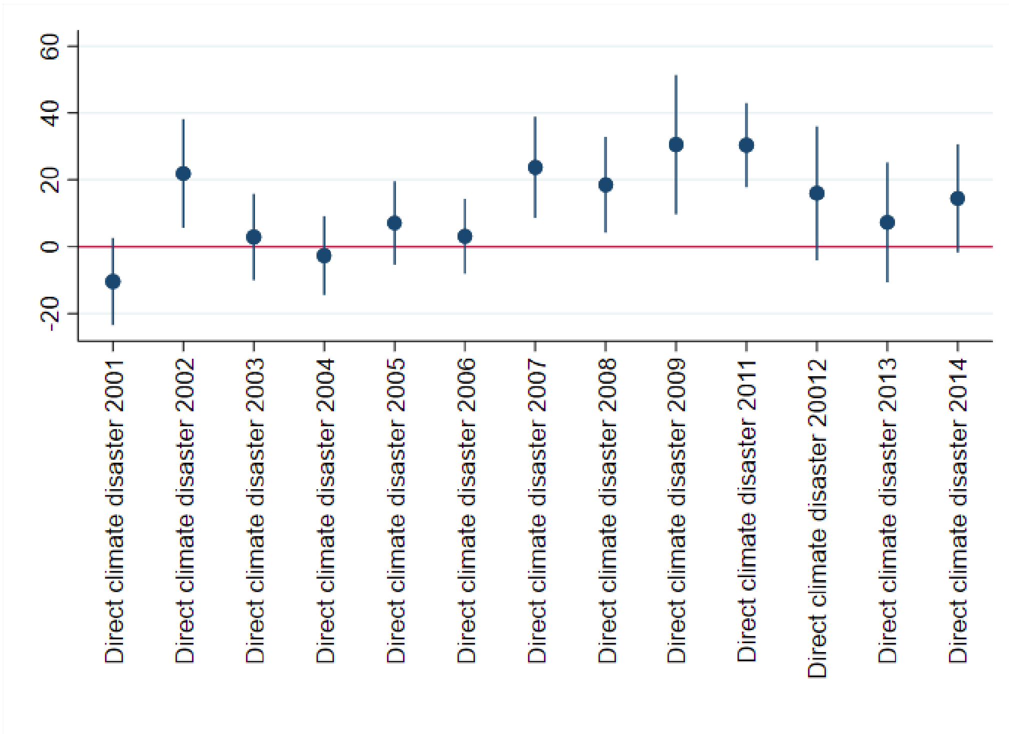
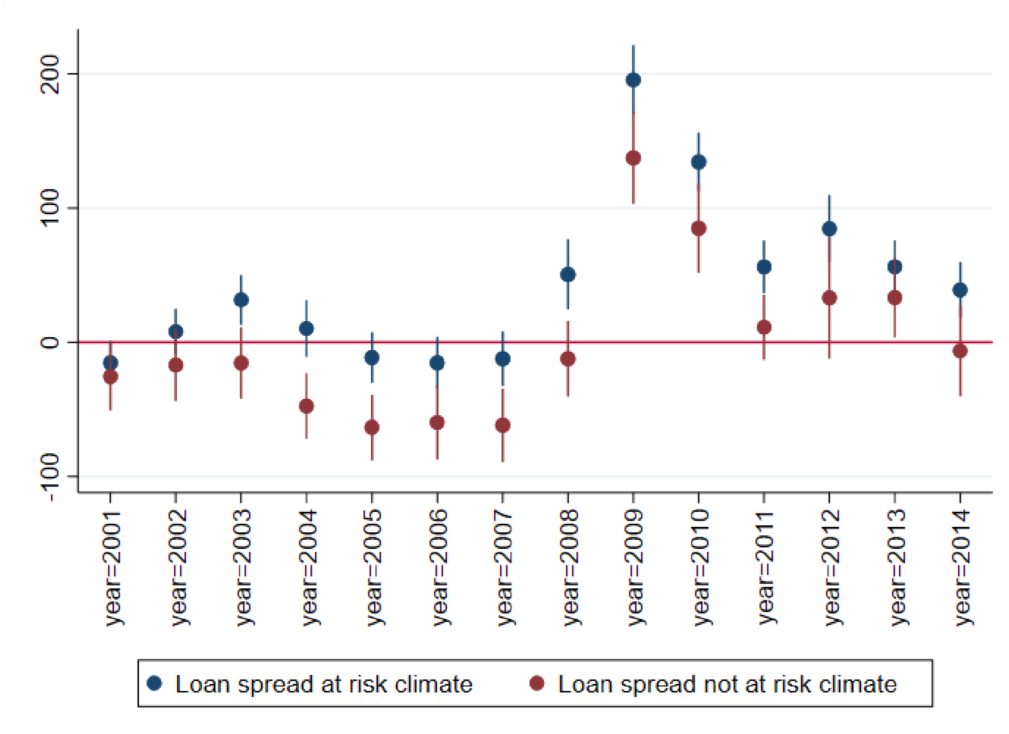


Figure 2: Figure
The figure presents coefficient estimates of loan interest rates on indirect exposure to climate and non-climate change disasters over time. Vertical bars represent 90% confidence intervals. While rates are largely similar in early years, they diverge around the year 2000 with climate change exposed firms paying on average about 40 basis points higher spread.



Tables

Table 1: Summary statistics
Panel A presents descriptive statistics for the sample of loans merged with borrower characteristics. All variables are explained in Appendix A.1. The sample contains new loan originations matched with lead lenders. All observations are counted by loan. Variables are defined in Appendix A.1. Panel B reports data on property losses from natural disasters. These data are at the county level and cover natural disasters reported in SHELDUS with aggregate damages exceeding $100 million in 2016 constant dollars. The sample period of loans and natural disasters is 1990 to 2014.

Panel A: Loan characteristics

	N	Mean	Std Dev	25th	Median	75th
Spread (bp)	23,951	166.26	124.38	62.50	143.75	244.06
Maturity (year)	23,951	3.75	1.93	2.00	4.00	5.00
Loan Amount ($ million)	23,951	770.40	1448.60	93.61	291.80	839.58
Financial Covenant (dummy)	23,951	0.56	0.50	0.00	1.00	1.00
Number of Financial Covenant	23,951	1.25	1.35	0.00	1.00	2.00
Term Loan	23,951	0.19	0.34	0.00	0.00	0.29
Revolving Loan	23,951	0.76	0.38	0.50	1.00	1.00
Borrower Total Asset ($ billion)	23,951	22.14	68.24	0.58	2.27	10.10
Borrower ROA	23,951	0.13	0.10	0.08	0.12	0.18
Borrower Debt to Asset	23,951	0.34	0.22	0.19	0.32	0.47
Indirect climate disasters	23,951	0.60	0.49	0.00	1.00	1.00
Indirect nonclimate disasters	23,951	0.51	0.50	0.00	1.00	1.00
Recent climate disasters	23,951	0.42	0.49	0.00	0.00	1.00
Recent nonclimate disasters	23,951	0.27	0.44	0.00	0.00	1.00
Customer disaster exposure	23,951	0.00	0.04	0.00	0.00	0.00
Supplier disaster exposure	23,951	0.01	0.07	0.00	0.00	0.00
Bank disaster exposure (% amount)	23,951	0.51	1.30	0.00	0.02	0.52
Bank disaster exposure (% incidence)	23,951	0.43	1.13	0.00	0.02	0.43

Panel B: Disaster Damages

Disaster Type	Number of Affected Counties	Total Property Damage across All Affected Counties ($B)	County Property Damage Distribution ($M)			
			p25	p50	p75	p95
Hurricane	1356	235.03	1.12	11.41	62.56	437.94
Tornado	237	15.79	1.14	6.74	31.10	249.36
Wildfire	226	15.51	0.19	4.25	4.25	229.13
Winter Weather	693	6.85	0.12	2.31	16.00	35.85
Flooding	1433	41.17	1.56	5.97	16.59	86.01
Earthquake	16	0.53	0.00	0.09	14.53	32.98

Table 2: Rates and climate change related disasters

This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters in this analysis are hurricanes. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. All specifications also include controls for the direct effect of disasters. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) climate change disasters				
	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × *Recent hurricane*	8.608**	8.097*	8.913**	8.574**
	(4.082)	(4.014)	(3.844)	(3.798)
Indirect hurricane	-1.382	-1.255	-1.546	-1.468
	(3.594)	(3.561)	(3.299)	(3.287)
Recent hurricane	3.104	3.518	1.304	1.601
	(5.339)	(5.314)	(4.948)	(4.949)
N	21,127	21,127	21,127	21,127
R^2	0.762	0.762	0.774	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table 3: Rates and non-climate change related disasters

This table reports regressions of loan spread on borrowers' indirect non-climate change related disaster dummy with the occurrence of the same type of disasters. Non-climate change related disasters in this analysis are earthquakes. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) non-climate change disasters				
	Spread			
	(1)	(2)	(3)	(4)
Indirect earthquake × *Recent earthquake*	-4.202	-3.498	-1.889	-1.391
	(7.216)	(7.258)	(6.513)	(6.581)
Indirect earthquake	-3.358	-3.440	-0.260	-0.336
	(4.675)	(4.615)	(4.415)	(4.389)
Recent earthquake	11.868**	11.541**	11.593**	11.373**
	(5.526)	(5.522)	(4.832)	(4.877)
N	21,127	21,127	21,127	21,127
R^2	0.762	0.762	0.774	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table 4: Climate change and non-climate change disasters jointly

This table reports regressions of loan spread on borrowers' indirect natural disaster dummies with the occurrence of the same type of disasters. Both climate and non-climate change related disasters are included, defined as hurricanes and earthquakes, respectively. *Direct disaster exposure* are deciles based on firms' aggregate footprints in counties affected by disasters. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) climate change and non-climate change disasters				
	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × *Recent hurricane*	10.432**	8.531**	9.308**	8.973**
	(4.310)	(3.962)	(3.820)	(3.781)
Indirect earthquake × *Recent earthquake*	-2.433	-3.481	-1.845	-1.348
	(7.905)	(7.243)	(6.490)	(6.563)
Indirect hurricane	-2.853	-1.482	-1.700	-1.622
	(3.990)	(3.565)	(3.302)	(3.290)
Indirect earthquake	-3.165	-3.392	-0.257	-0.328
	(4.792)	(4.589)	(4.406)	(4.380)
Recent hurricane	4.404	4.022	1.862	2.151
	(5.179)	(5.284)	(4.942)	(4.944)
Recent earthquake	14.360**	12.785**	12.523**	12.329**
	(5.927)	(5.418)	(4.721)	(4.749)
N	21,127	21,127	21,127	21,127
R^2	0.736	0.762	0.775	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Table 5: Cross sectional effects on high risk borrowers

This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters in this analysis are hurricanes. *High leverage* is an indicator equal to 1 for firms with leverage in the fourth quartile. $Non-investment\ grade$ is an indicator equal to one for firms with a senior unsecured credit rating below investment grade (BBB). Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. Other interactions include all omitted interactions and individual coefficients for the triple interactions. All variables are explained in Appendix A.1. All specifications also include controls for the direct effect of disasters. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) and high risk borrowers		
	Spread	
	(1)	(2)
Indirect hurricane × *Recent hurricane*	4.437	6.010
	(4.479)	(5.196)
Indirect hurricane × *Recent hurricane* × *High leverage*	21.538*	
	(11.497)	
Indirect hurricane × *Recent hurricane* × $Non-investment\ grade$		26.669**
		(12.915)
N	21,127	21,127
R^2	0.772	0.774
Direct Disaster Exposure	Yes	Yes
Bank × Year FE	Yes	Yes
Firm FE	Yes	Yes
Loan controls	Yes	Yes
Firm controls	Yes	Yes
Other interactions	Yes	Yes

Table 6: Effects and disaster size

This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters include hurricanes. Loan-level and firm-level controls include loan type and covenant indicators, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) and disaster size		
	Spread	
	(1)	(2)
$Indirect\ hurricane \times Recent\ hurricane_{100mil}$	8.574**	
	(3.798)	
$Indirect\ hurricane \times Recent\ hurricane_{200mil}$		10.335**
		(3.869)
N	21,127	21,127
R^2	0.775	0.775
Direct Disaster Exposure	Yes	Yes
Bank× Year FE	Yes	Yes
Firm FE	Yes	Yes
Loan controls	Yes	No
Firm controls	No	Yes

Table 7: Climate change risk in the secondary market

This table reports regressions of log of loan average quote price in the secondary market on borrowers' indirect hurricane risk dummy with the occurrence of hurricanes. Parentheses contain t-statistics calculated from standard errors clustered by loan. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Quote price in the secondary market				
	Log Average Quote			
	(1)	(2)	(3)	(4)
Indirect hurricane × *Recent hurricane*	-0.016*	-0.016***	-0.023**	-0.017***
	(0.010)	(0.005)	(0.010)	(0.005)
Indirect hurricane	-0.004	-0.014	-0.017	-0.043***
	(0.017)	(0.015)	(0.017)	(0.014)
Recent hurricane	0.010***	0.018***	0.022***	0.024***
	(0.003)	(0.003)	(0.004)	(0.003)
Direct disaster	-0.013	-0.037***	0.023*	-0.008**
	(0.011)	(0.006)	(0.013)	(0.004)
N	80,103	80,018	80,103	80,018
R^2	0.001	0.817	0.082	0.846
Loan FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes

Table 8: Time varying attention to climate change and rates

This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters are hurricanes. *IPCC* is a time dummy for periods within 24 months after the release of the third (in 2001), the fourth (in 2007), and the fifth (in 2013) IPCC reports. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) and IPCC reports				
	Spread			
	(1)	(2)	(3)	(4)
Indirect exposure hurricane × *Recent hurricane*	15.855**	24.938***	17.670*	17.315*
×*IPCC*	(7.493)	(8.578)	(8.611)	(8.684)
Indirect exposure hurricane × *Recent hurricane*	9.627*	7.205	8.727**	8.412**
	(4.830)	(4.216)	(3.954)	(3.933)
N	21,127	21,127	21,127	21,127
R^2	0.736	0.763	0.775	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes
Other interactions	Yes	Yes	Yes	Yes

Table 9: Are the pricing effects permanent?

This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters include hurricanes. Loan-level and firm-level controls include loan type and covenant indicators, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Development of rates over time				
	Spread			
	(1)	(2)	(3)	(4)
$Indirect\ hurricane \times Recent\ hurricane_{4\ quarters\ prior}$	8.517	8.315	13.313	13.198
	(7.864)	(7.862)	(8.717)	(8.759)
$Indirect\ hurricane \times Recent\ hurricane_{3\ quarters\ prior}$	9.141	8.731	8.623	8.395
	(8.503)	(8.392)	(9.541)	(9.453)
$Indirect\ hurricane \times Recent\ hurricane_{2\ quarters\ prior}$	5.045	5.777	9.740	10.234
	(10.605)	(10.619)	(10.136)	(10.189)
$Indirect\ hurricane \times Recent\ hurricane_{1\ quarter\ prior}$	-3.546	-3.794	-3.347	-3.504
	(6.816)	(6.776)	(7.012)	(6.954)
$Indirect\ hurricane \times Recent\ hurricane$	10.801**	10.594**	11.447**	11.315**
	(4.698)	(4.630)	(4.471)	(4.420)
$Indirect\ hurricane \times Recent\ hurricane_{1\ quarter\ future}$	0.886	0.720	1.983	1.873
	(6.114)	(6.086)	(5.938)	(5.924)
$Indirect\ hurricane \times Recent\ hurricane_{2\ quarters\ future}$	3.967	4.324	3.395	3.648
	(5.311)	(5.307)	(5.680)	(5.683)
$Indirect\ hurricane \times Recent\ hurricane_{3\ quarters\ future}$	4.468	4.690	6.348	6.493
	(6.075)	(6.147)	(5.590)	(5.658)
$Indirect\ hurricane \times Recent\ hurricane_{4\ quarters\ future}$	0.680	0.196	0.661	0.350
	(5.195)	(5.091)	(5.065)	(4.998)
N	21,127	21,127	21,127	21,127
R^2	0.762	0.762	0.775	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes
Other interactions	Yes	Yes	Yes	Yes

Table 10: The dynamic pricing of climate change risk in the secondary market
This table reports regressions of log of loan average quote price in the secondary market on borrowers' indirect hurricane risk dummy with dummies indicating weeks after the occurrence of hurricanes. Parentheses contain t-statistics calculated from standard errors clustered by loan. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Development of secondary market price over time				
	Log Average Quote			
	(1)	(2)	(3)	(4)
Indirect hurricane × *Week_0*	-0.012	-0.015***	-0.018	-0.016***
	(0.014)	(0.006)	(0.014)	(0.006)
Indirect hurricane × *Week_1*	-0.020	-0.028***	-0.022	-0.026***
	(0.021)	(0.009)	(0.021)	(0.009)
Indirect hurricane × *Week_2*	-0.020**	-0.020***	-0.025***	-0.021***
	(0.010)	(0.007)	(0.010)	(0.007)
Indirect hurricane × *Week_3*	-0.029**	-0.013**	-0.045***	-0.019***
	(0.014)	(0.006)	(0.014)	(0.006)
Indirect hurricane × *Week_4*	-0.001	-0.002	-0.019***	-0.008*
	(0.007)	(0.004)	(0.007)	(0.004)
Indirect hurricane × *Week_5*	0.004	-0.005	-0.010	-0.009***
	(0.008)	(0.004)	(0.008)	(0.003)
Indirect hurricane × *Week_6*	-0.005	0.006	-0.025**	-0.002
	(0.010)	(0.004)	(0.010)	(0.003)
Indirect hurricane × *Week_7*	0.004	0.012**	-0.010	0.006
	(0.009)	(0.006)	(0.008)	(0.005)
Indirect hurricane	-0.004	-0.014	-0.014	-0.043***
	(0.016)	(0.015)	(0.016)	(0.014)
Direct disaster	-0.011	-0.037***	0.023*	-0.010***
	(0.011)	(0.006)	(0.013)	(0.004)
N	80,103	80,018	80,103	80,018
R^2	0.002	0.817	0.082	0.846
Loan FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes

Table 11: Bank disaster exposures and rates

This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters include hurricanes. *Bank disaster exposure* is the ratio of a bank's outstanding loans that are assigned to disaster firms, measured either by loan amount or loan incidence. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) and bank disaster exposures				
	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × *recent hurricane*	9.642**	8.366**	9.793**	8.476**
	(4.344)	(3.721)	(4.319)	(3.728)
Bank disaster exposure (*loan incidence*)	2.899*	2.009		
	(1.495)	(1.338)		
Bank disaster exposure (*loan amount*)			2.851*	1.857
			(1.426)	(1.293)
N	21,127	21,127	21,127	21,127
R^2	0.736	0.775	0.736	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	Yes	No	Yes

Table 12: Economic links between borrowers and rates

This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters include hurricanes, floods, and wildfires. *Customer disaster exposure* and *Supplier disaster exposure* are a borrower's exposure through its customers and suppliers to natural disasters, respectively. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in bp) and economic links						
	Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
Indirect hurricane × *Recent hurricane*	9.939**	8.568**	9.682**	8.412**	9.678**	8.406**
	(4.396)	(3.800)	(4.400)	(3.772)	(4.404)	(3.773)
Customer disaster exposure	3.503	5.436			3.216	5.248
	(18.730)	(13.028)			(18.793)	(13.077)
Supplier disaster exposure			-29.549**	-18.776	-29.539**	-18.760
			(12.717)	(11.129)	(12.739)	(11.147)
N	21,127	21,127	21,127	21,127	21,127	21,127
R^2	0.735	0.775	0.736	0.775	0.736	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes

Table 13: Firm investment and cash reserves and climate change risk

This table reports regressions of investment on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters include hurricanes, floods, and wildfires. Firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	CapEx/Lagged Asset (%)			Cash / Liabilities (%)		
$Indirect\ hurricane \times Recent\ hurricane$	0.017	0.034	0.015	-1.888*	-1.907	-1.539
	(0.095)	(0.051)	(0.044) N	(1.113)	(1.223)	(1.125)
$Indirect\ hurricane \times recent\ hurricane \times non - investment\ grade$	-0.263**	-0.280***	-0.265**	2.354*	2.164*	2.294*
	(0.109)	(0.100)	(0.104)	(1.258)	(1.253)	(1.284)
N	332,670	332,670	287,181	309,045	309,045	291,036
R^2	0.423	0.453	0.507	0.593	0.595	0.657
Direct Disaster Exposure	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quater FE	No	Yes	Yes	No	Yes	Yes
Firm controls	No	No	Yes	No	No	Yes
Other interactions	Yes	Yes	Yes	Yes	Yes	Yes

Appendix for
"The rising tide lifts some interest rates: climate change, natural disasters, and loan pricing"

A.1 Variable Definitions

Loan Variables	
Loan Amount	Logarithm of loan amount in dollars, adjusted to 2016 values
Maturity (Years)	The number of years between loan start and end dates
Spread (bp)	The all-in-drawn spread in basis points
Term Loan	Indicator equal to one if the loan type is term loan
Revolving Loan	Indicator equal to one if the loan type is revolver
Financial Covenant (dummy)	Indicator equal to one if the loan contract includes covenants
Number of Financial Covenant	The number of covenants in a loan contract
Disaster Variables	
$Indirect\ climate\ disasters_{i,t}$	Indicator equal to one if firm i in the top quartile when we rank firms in month t by their location-weighted exposure to top 10% climate disasters in the past 10 years. Climate disasters include hurricanes, flooding, and wildfires.
$Indirect\ nonclimate\ disasters_{i,t}$	Indicator equal to one if firm i in the top quartile when we rank firms in month t by their location-weighted exposure to top 10% non-climate disasters in the past 10 years. Non-climate disasters include tornadoes, earthquakes, and winter weather.
$Recent\ climate\ disaster_t$	Indicator equal to one if climate disasters occur during $t-3$ to t.
$Recent\ nonclimate\ disaster_t$	Indicator equal to one if non-climate disasters occur during $t-3$ to t.
Other Variables	
$Bank\ disaster\ exposure_{m,t}$	Bank m's exposure to natural disasters that occur during $t-3$ to t. It is the ratio of the bank's outstanding loans, when a disaster occurs, that are assigned to disaster firms, measured either by loan amount or loan incidence.
$Customer\ disaster\ exposure_{i,t}$	Firm i's exposure through customers to natural disasters that occur during $t-3$ to t. It is the ratio of sales to disaster customers to the firm's total sales in the same quarter.

Supplier disaster exposure$_{i,t}$	Firm i's exposure through suppliers to natural disasters that occur during $t-3$ to t. It is the ratio of the sales from disaster suppliers to those suppliers' total sales in the same quarter.

A.2 Anecdotal evidence

This section provides anecdotal evidence that the link between climate change, natural disasters and credit risk is well understood for financial market participants and impacts bank's lending decisions.

As a first overview, we collect evidence from the 2019 10-K filings of 10 major U.S. banks (by assets). We present an overview of this analysis in Appendix Table A.1. As a first pass, we report whether the 10-K explicitly mentions climate change and natural disasters (or severe weather) in close proximity. Out of the ten banks, all but Morgan Stanley explicitly mention these two topics. Next, we look for any mentioning of a link between increasing severity and frequency of these disasters and climate change. Out of the 9 banks that remain, all but Wells Fargo explicitly state that there is a potential link between climate change and worsening severe weather incidents. In the last column of Appendix Table A.1 we report specific natural disasters mentioned in the context of climate change. Four banks mention specific disasters, with all of them mentioning hurricanes and/or storms. In addition, both Bank of America and JP Morgan Chase reference the risk of wild fires, and JP Morgan Chase mentions floods.

These results show that banks widely consider a link between climate change and natural disasters. In addition, the specific mentioning of hurricanes, wildfires and floods reassures our selection of climate change disasters. Below we present a selection of specific quotes from these 10-K filings, as well as other industry documents, that corroborate the attention to climate change disasters for credit market participants. These excerpts show that lenders incorporate climate change induced disaster risk into their lending decisions. **Bold text** presents particularly relevant statements highlighted by us.

1. Quotes from JPMorgan Chase 2019 10-K:
   "JPMorgan Chase operates in many regions, countries and communities around the world where its businesses, and the activities of its clients and customers, could be disrupted by climate change. Potential physical risks from climate change may include:

   - altered distribution and intensity of rainfall
   - prolonged droughts or flooding
   - increased frequency of wildfires
   - rising sea levels
   - rising heat index

   These climate driven changes could have a material adverse impact on asset values and the financial performance of JPMorgan Chase's businesses, and those of its clients and customers."

2. Quotes from Bank of America's 2018 carbon disclosure project report:
   " There is scientific consensus that flood risks are increasing in many regions due to climate change. [...] **We conduct an annual assessment of physical risks to our facilities from factors including severe weather, wildfires and flooding.**"

3. Quotes from Citi's 2019 10-K:
   "**Climate change presents immediate and long-term risks to Citi and to its clients and customers, with the risks potentially increasing over time.** Climate risk can arise from physical risks (risks related to the physical effects of climate change) [...] **Citi's Environmental and Social Risk Management Policy incorporates climate risk assessment for credit underwriting purposes.**"

4. Quotes from Goldman Sachs' 2019 10-K:
   "Climate change may cause extreme weather events that disrupt operations at one or more of our primary locations, which may negatively affect our ability to service and interact with our clients, and also may adversely affect the value of our investments, including our real estate investments. **Climate change may also have a negative impact on the financial condition of our clients, which may decrease revenues from those clients and increase the credit risk associated with loans** and other credit exposures to those clients."

5. Quotes from U.S. Bancorp' 2019 10-K:
   "[...] **the force and frequency of natural disasters are increasing as the climate changes.**"

6. Quotes from Truist's 2018 10-K:
   "[BB&T's operations and customers] could be adversely impacted by such events in those regions, **the nature and severity of which may be impacted by climate change** and are difficult to predict. These and other unpredictable natural disasters could have an adverse effect on BB&T in that such events could materially disrupt its operations or the ability or willingness of its customers to access the financial services offered by BB&T"

7. Quotes from PNC's 2019 10-K:
   "Climate change may be increasing the frequency or severity of adverse weather conditions, making the impact from these types of natural disasters on us or our customers worse. [...] **we could face reductions in creditworthiness on the part of some customers or in the value of assets securing loans.**"

8. Quotes from TD Bank's 2019 10-K:
   "Climate change risk has emerged as one of the top environmental risks for the Bank as extreme weather events, shifts in climate norms, and the global transition to a low carbon economy risks increase and evolve."

9. Quotes from Deutsche Bank's 2018 White Paper on Climate Change:
   "We believe investors have no place to hide when it comes to the effects of physical climate change since even if emissions were cut to zero tomorrow, **society will still face intensifying extreme weather events over the next several decades.** [...] **Perhaps the most telling metric of a company's climate risk is the location of its assets and their exposure to changing extreme weather patterns. The geographic areas on which a company depends to produce, manufacture, deliver, and sell goods, are a powerful indicator of its fundamental exposure to future climate risks. [...] Financial risk can go beyond recovering from an extreme weather event. Even a company that was not directly affected might be financially impacted. For example, through a gradual increase in its operational expenses due to rising insurance costs, a default in bank loans or other debt, or at a more macro-level, lower consumption levels.**"

Lenders are not the only market participants that connect climate change to severe weather and credit risk. Both Standard and Poor's as well as Moody's Investor Services have released documents detailing their pricing of climate change induced severe weather:

1. Quotes from Standard and Poor's 2017 climate change report:
   "We know that climate change will increase the incidence and severity of weather events, both chronic and acute, such as hurricanes and droughts. [..] Severe weather conditions lead to flooding of a large part of the

construction site at the end of December 2015 and beginning of January 2016. [...] On Feb. 14, 2017, we lowered the Aberdeen Roads (Finance) plc rating to 'BBB+' from 'A-' [...]"

2. Quotes from Moody's 2020 research note on U.S. utilities:
   "As climate change increases the frequency and severity of extreme weather events, anticipation of these hazards will be increasingly reflected in the capital investment programs of utilities."
3. Quotes from Moody's 2017 research note on U.S. state and local government bonds:
   "The report differentiates between climate trends, which are a longer-term shift in the climate over several decades, versus **climate shock, defined as extreme weather events like natural disasters, floods, and droughts which are exacerbated by climate trends.** Our credit analysis considers the effects of climate change when we believe a meaningful credit impact is highly likely to occur and not be mitigated by issuer actions, even if this is a number of years in the future. "

Quotes from United States Fourth National Climate Assessment:

1. "The National Oceanic and Atmospheric Administration estimates that **the United States has experienced 44 billion-dollar weather and climate disasters since 2015** (through April 6, 2018), incurring costs of nearly $400 billion."
2. **"Since 1980, the number of extreme weather-related events per year costing the American people more than one billion dollars per event has increased significantly (accounting for inflation), and the total cost of these extreme events for the United States has exceeded $1.1 trillion."**
3. The report specifically mentions hurricanes, floods, droughts and wildfires, as well as tornadoes and heat waves

On an intnernational level, the United Nations Environment Programme Finance Initiative (UNEP FI) addresses the issue:

1. Quotes from United Nations Environment Programme Finance Initiative 2018 Navigating a New Climate Report:
   "**To date, risks and opportunities resulting from the physical impacts of climate change (due to more frequent and extreme weather and climate events, and gradual shifts in climate patterns) have received attention within the insurance sector, but have not been widely assessed in credit and lending portfolios held by banks.** [...] Extreme events represent acute climate variability and may only occur in specific locations, such as floodplains or tropical cyclone regions. **The extreme events covered in the methodologies are: cyclone, flood, wildfire, drought and extreme heat.**"

Table A.1: Climate change related disasters in banks' 10-K filings

This Table reports a summary of the degree to which the 10 largest U.S. banks by assets mention climate change in their 2019 annual reports. The column "climate disasters" reports if these filings mention severe weather or natural disasters in the context of climate change broadly. The second column, "worsening trend" reports if the filings mention a potential increase in severity of these disasters due to climate change. The final column, "specific disasters", reports which specific types of severe weather are mentioned in this context, if any.

Bank	Climate disasters	Worsening trend	Specific disasters
JPMorgan Chase	Yes	Yes	Flooding, wildfire, heat, storm
Bank of America	Yes	Yes	Fire, hurricanes
Citi	Yes	Yes	None
Wells Fargo	Yes	No	Hurricanes
Goldman Sachs	Yes	Yes	None
Morgan Stanley	Yes	No	None
U.S. Bankcorp	Yes	Yes	None
Truist	Yes	Yes	Hurricanes, storms
PNC	Yes	Yes	None
TD Bank	Yes	Yes	None

Table A.2: Floods and rates

This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters include floods. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in basis points)				
	Spread			
	(1)	(2)	(3)	(4)
Indirect flooding × *Recent flooding*	9.820*	9.649*	8.984*	8.848*
	(4.820)	(4.741)	(4.437)	(4.358)
Indirect flooding	-2.562	-2.490	-1.973	-1.927
	(4.043)	(3.995)	(3.702)	(3.676)
Recent flooding	-6.794**	-6.895**	-5.929**	-5.994**
	(2.634)	(2.640)	(2.633)	(2.655)
N	21127	21127	21127	21127
R^2	0.762	0.762	0.774	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.3: Fires and rates

This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters include wild fires. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in basis points)				
	Spread			
	(1)	(2)	(3)	(4)
$Indirect\ fire \times Recent\ fire$	9.701**	9.668**	7.635*	7.632*
	(4.081)	(4.006)	(4.019)	(3.961)
$Indirect\ fire$	-3.789	-3.900	-1.489	-1.572
	(2.689)	(2.654)	(2.568)	(2.560)
$Recent\ fire$	-7.003*	-6.908	-5.254	-5.200
	(4.038)	(4.042)	(4.081)	(4.092)
N	21127	21127	21127	21127
R^2	0.762	0.762	0.774	0.774
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.4: Winter weather and rates

This table reports regressions of loan spread on borrowers' indirect non-climate change related disaster dummy with the occurrence of the same type of disasters. Non-climate change related disasters include winter weather. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Rates (in basis points)			
Indirect winter_weather × *Recent winter_weather*	-5.295	-5.346	-2.941	-2.977
	(9.342)	(9.331)	(8.322)	(8.305)
Indirect winter_weather	9.573***	9.611***	9.188***	9.195***
	(3.083)	(3.039)	(2.757)	(2.761)
Recent winter_weather	9.840*	9.804*	8.264	8.248
	(5.747)	(5.677)	(5.655)	(5.609)
N	21127	21127	21127	21127
R^2	0.762	0.762	0.775	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.5: Tornadoes and rates

This table reports regressions of loan spread on borrowers' indirect non-climate change related disaster dummy with the occurrence of the same type of disasters. Non-climate change related disasters include tornadoes. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Rates (in basis points)			
Indirect tornado × *Recent tornado*	7.333	7.383	8.501*	8.546*
	(4.459)	(4.442)	(4.317)	(4.309)
Indirect tornado	-3.163	-3.154	-2.885	-2.899
	(3.697)	(3.673)	(3.403)	(3.393)
Recent tornado	-6.431*	-6.395*	-7.640**	-7.628**
	(3.468)	(3.471)	(3.497)	(3.505)
N	21127	21127	21127	21127
R^2	0.762	0.762	0.774	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.6: Climate disasters and rates (climate aggregated)

This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters include hurricanes, floods, and wildfires. *Direct disaster exposure* are deciles based on firms' aggregate footprints in counties attacked by disasters. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in basis points)				
	Spread			
	(1)	(2)	(3)	(4)
Indirect disasters × *Recent disasters*	8.109***	6.460**	7.308**	6.045**
	(2.664)	(2.493)	(2.689)	(2.557)
Indirect disasters	-4.756*	-2.906	-4.282*	-2.683
	(2.643)	(2.374)	(2.448)	(2.224)
Recent disasters	-0.164	-0.666	-0.980	-1.439
	(3.402)	(3.357)	(3.267)	(3.237)
N	21127	21127	21127	21127
R^2	0.735	0.762	0.753	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.7: Non-climate disasters and rates (non-climate aggregated)

This table reports regressions of loan spread on borrowers' indirect non-climate change related disaster dummy with the occurrence of the same type of disasters. Non-climate change related disasters include tornadoes, winter weather, and earthquakes. *Direct disaster exposure* are deciles based on firms' aggregate footprints in counties attacked by disasters. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in basis points)				
	Spread			
	(1)	(2)	(3)	(4)
Indirect disasters × *Recent disasters*	4.224	3.234	5.537	4.415
	(3.427)	(3.765)	(3.559)	(3.787)
Indirect disasters	2.844	4.319	4.332	5.504
	(4.023)	(3.729)	(3.667)	(3.489)
Recent disasters	2.360	1.706	0.976	0.604
	(4.114)	(3.807)	(4.021)	(3.783)
N	21127	21127	21127	21127
R^2	0.735	0.762	0.753	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.8: All disaster types and rates (climate and non-climate aggregated)
This table reports regressions of loan spread on borrowers' indirect natural disaster dummies with the occurrence of the same type of disasters. Both climate and non-climate change related disasters are included. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in basis points)				
	Spread			
	(1)	(2)	(3)	(4)
Indirect climate disasters	8.215***	6.515**	6.264**	6.102**
×*Recent climate disasters*	(2.723)	(2.559)	(2.672)	(2.627)
Indirect non − climate disasters	4.470	3.459	4.526	4.588
×*Recent non − climate disasters*	(3.581)	(3.802)	(3.819)	(3.844)
Indirect climate disasters	-5.032*	-3.253	-3.055	-3.070
	(2.533)	(2.290)	(2.147)	(2.138)
Indirect non − climate disasters	3.124	4.454	5.604	5.606
	(4.028)	(3.750)	(3.524)	(3.516)
Recent climate disasters	0.470	-0.134	-1.104	-0.984
	(3.168)	(3.095)	(3.020)	(3.018)
Recent non − climate disasters	2.834	1.996	0.827	0.773
	(4.090)	(3.737)	(3.713)	(3.679)
N	21127	21127	21127	21127
R^2	0.736	0.762	0.775	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.9: Effects and disaster size (climate aggregated)
This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters include hurricanes, floods, and wildfires. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All specifications include controls for the direct effect of disasters. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates				
	Spread			
	(1)	(2)	(3)	(4)
Indirect disasters × *Recent disasters_50mil*	2.829			-8.291
	(2.410)			(5.395)
Indirect disasters × *Recent disasters_100mil*		5.721**		0.675
		(2.542)		(6.897)
Indirect disasters × *Recent disasters_200mil*			8.571***	15.104**
			(2.717)	(5.808)
Indirect disasters	-2.251	-2.786	-3.140	-2.291
	(2.146)	(2.183)	(2.195)	(2.140)
N	21127	21127	21127	21127
R^2	0.774	0.774	0.775	0.775
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.10: Climate disasters and rates (employment weighted operations)
All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in basis points)				
	Spread			
	(1)	(2)	(3)	(4)
Indirect disasters × *Recent disasters*	7.276**	6.403**	7.110**	6.410**
	(3.285)	(2.990)	(3.036)	(2.822)
Indirect disasters	-3.462	-1.704	-3.296	-1.801
	(3.590)	(3.425)	(3.218)	(3.070)
Recent disasters	0.132	-0.612	-0.933	-1.560
	(3.560)	(3.404)	(3.351)	(3.234)
N	21127	21127	21127	21127
R^2	0.735	0.762	0.753	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.11: Robustness: *Indirect disaster* defined by the top quintile (climate aggregated)
This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters include hurricanes, floods, and wildfires. We classify firms as indirectly exposed to each type of disasters if its operations weighted exposure to historically disaster prone counties is in the top quintile (rather than quartile) of firms. *Direct disaster exposure* are deciles based on firms' aggregate footprints in counties attacked by disasters. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in basis points)				
	Spread			
	(1)	(2)	(3)	(4)
Indirect disasters × *Recent disasters*	8.429***	6.065**	7.674***	5.719**
	(2.661)	(2.538)	(2.711)	(2.648)
Indirect disasters	-6.551**	-4.476	-5.327*	-3.572
	(2.863)	(2.779)	(2.600)	(2.501)
Recent disasters	0.104	-0.259	-0.762	-1.073
	(3.520)	(3.413)	(3.339)	(3.259)
N	21127	21127	21127	21127
R^2	0.736	0.762	0.753	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Table A.12: Robustness: historical exposure defined by the top 20% in the past 10 years (climate aggregated) This table reports regressions of loan spread on borrowers' indirect climate change related disaster dummy with the occurrence of the same type of disasters. Climate change related disasters include hurricanes, floods, and wildfires. We classify counties as high-exposure counties if they are located in the top 20% of counties with respect to damages for a certain type of disaster within 10 year rolling window. *Direct disaster exposure* are deciles based on firms' aggregate footprints in counties attacked by disasters. Loan-level and firm-level controls include loan type and covenant dummies, loan maturity, borrower total asset, ROA, and debt over asset ratio. All variables are explained in Appendix A.1. Parentheses contain t-statistics calculated from standard errors double clustered by firm and year. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Rates (in basis points)				
	Spread			
	(1)	(2)	(3)	(4)
Indirect disasters × Recent disasters	7.937**	7.941**	7.607**	7.826**
	(3.119)	(3.145)	(3.238)	(3.247)
Indirect disasters	-3.727	-3.169	-3.189	-2.693
	(3.112)	(2.860)	(2.919)	(2.738)
Recent disasters	-0.123	-1.154	-1.095	-2.031
	(3.122)	(3.182)	(2.997)	(3.056)
N	21127	21127	21127	21127
R^2	0.735	0.762	0.753	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes